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Digital transformation and income gaps in Vietnam's labor market

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ABSTRACT

This study examines the impact of digital transformation and personal characteristics on income disparities between formal and informal workers in Vietnam. Such disparities mainly arise from differences in benefits, qualifications, career opportunities, and access to digital technologies. Using data from the Labor Force Survey (LFS) together with the provincial ICT index, the study applies quantile regression and the Machado–Mata decomposition method. The results show that education, gender, and digital skills significantly influence income, while the effect of provincial ICT indicators remains limited, especially for informal workers. This indicates that Vietnam's digital transformation has so far focused more on infrastructure, with less direct impact on business activities or job accessibility. In addition, the findings reveal that formal workers earn more at lower income levels, but at higher quantiles, informal workers perform better due to their flexibility and market adaptability. The novelty of this study lies in combining micro labor data with a provincial digital transformation index to analyze income gaps between the two labor sectors. It provides empirical evidence of the limited effectiveness of current digital transformation efforts and suggests several policy directions to improve skills, reduce inequality, and promote more inclusive digital development.

Contribution/ Originality: The research is distinctive in bringing together labor force microdata and regional indicators of digital transformation. Through the Machado–Mata decomposition, it sheds light on income disparities across labor sectors and reveals the uneven inclusiveness of Vietnam's ongoing digitalization.

1. INTRODUCTION

Informal workers include self-employed individuals or business owners without official registration, unpaid family workers, and wage earners without labor contracts or compulsory social insurance coverage (General Statistics Office of Vietnam (GSO), 2022). Informal workers exist as an objective necessity in every economy. Notably, during economic shocks, the informal sector serves as a support mechanism for the economy, acting as a temporary safety net to address employment challenges (General Statistics Office of Vietnam (GSO), 2022). However, due to the absence of income protection and social security policies, the expansion of this sector can heighten economic vulnerability. Figure 1 illustrates that, between 2018 and 2023, 77.5% to 83.3% of unskilled workers were employed in the informal sector. This highlights the concentration of vulnerable workers in this sector. Enhancing technical expertise and improving personal characteristics related to productivity for informal workers are critical solutions to narrowing the income gap between workers in the formal and informal sectors.

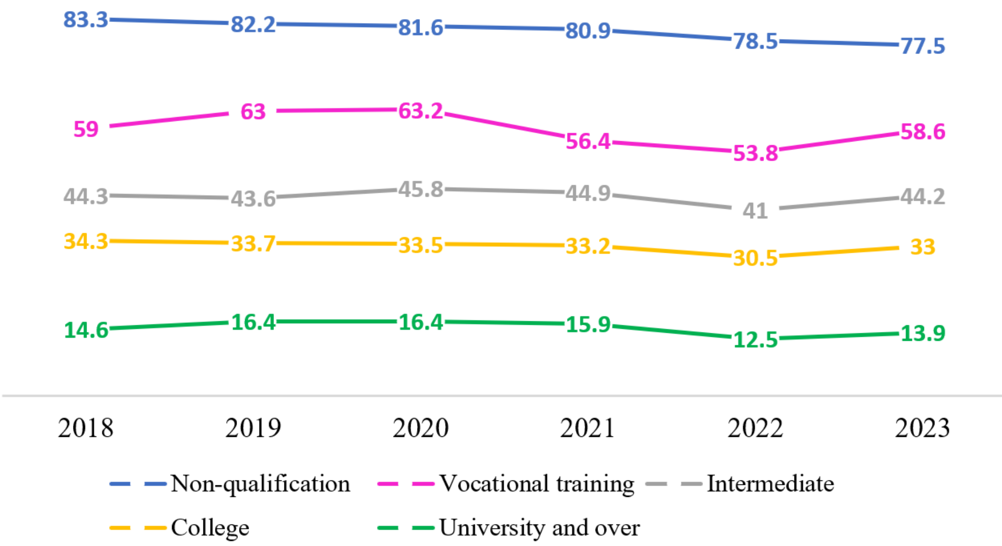

Figure 1. Informal employment rate by qualification.

Source: gso.gov.vn

Alongside workers' personal characteristics, digital transformation has become an inevitable trend in the modern economy and exerts a profound influence on employment. However, its benefits have not been evenly distributed. While some workers gain advantages thanks to higher qualifications and digital skills, others face difficulties due to limited access or weaker adaptability.

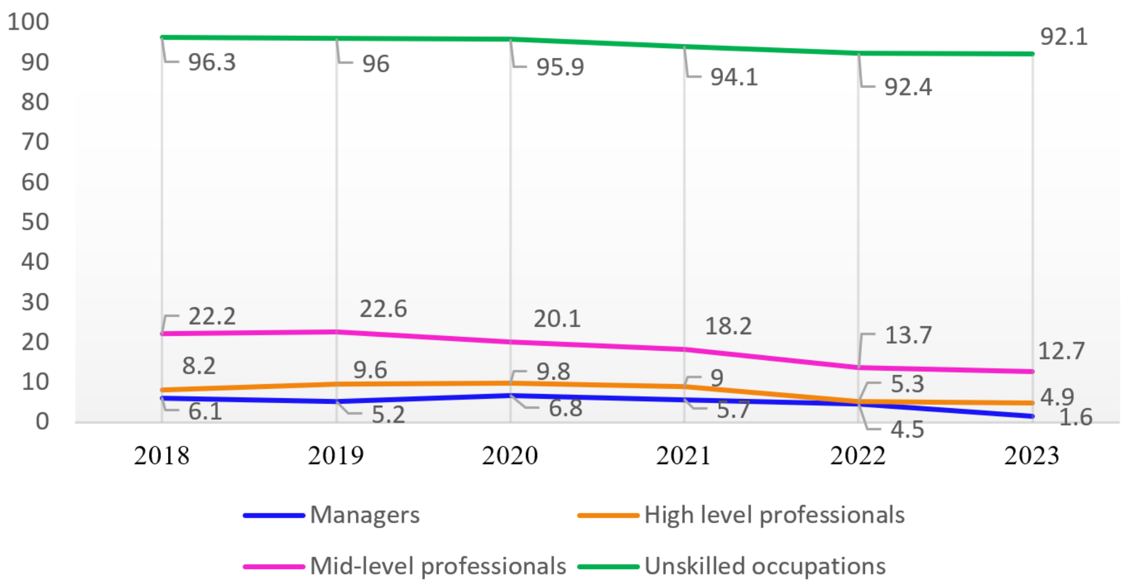

Figure 2. Informal employment rate by occupation.

Source: gso.gov.vn.

Figure 2 shows that during 2018–2023, more than 92% of unskilled occupations were concentrated in the informal sector, meaning that less than 8% were in the formal sector. In contrast, high-income or highly skilled occupations, such as management or technical expertise, were predominantly found in the formal sector, which accounted for 93.9% to 98.4%. This significant disparity highlights the limited opportunities and suboptimal working conditions faced by informal workers and emphasizes the need for targeted policies to reduce inequality in the labor market.

Differences in education levels and occupations between the formal and informal sectors directly affect workers' livelihoods and create broader social consequences, such as rising inequality, unbalanced development, and potential risks of social instability. Against this background, the present study aims to assess the impact of digital transformation and individual characteristics on income disparities between formal and informal workers. A key novelty is the combination of microdata from the Labor Force Survey with the provincial ICT index, which enables analysis of both personal factors and local digital conditions. The findings are expected to provide empirical evidence and policy recommendations to promote a more inclusive and equitable digital transformation.

2. LITERATURE REVIEW

2.1. The Relationship Between Digital Transformation, Personal Characteristics, and Workers' Income

Digital transformation is generally understood as the application of digital technologies to reshape business activities and social life. Scholars emphasize that it is not only about digitization but a broader process that brings fundamental changes to firms, markets, and even society (Demirkan, Spohrer, & Welser, 2016; Vial, 2021). In essence, digital transformation involves reconfiguring processes, capabilities, and models to take advantage of technological progress. Many countries and firms have therefore prioritized digital transformation as a key driver of innovation and growth. Nonetheless, its implementation still varies widely across countries and sectors, depending on development conditions and available resources (Gonçalves, Da Silva, & Ferreira, 2022).

When examining the relationship between digital transformation and employee earnings, many studies conclude that digital transformation positively impacts earnings in certain fields (Caselli & Manning, 2019; Genz, Janser, & Lehmer, 2019; Lim & Han, 2018). Shair, Zahra, Tayyab, and Kubra (2022) in a study on employee wages in Pakistan, it was emphasized that individuals proficient in digital skills earn more than those lacking such skills. Genz et al. (2019), while studying the relationship between digital transformation and wages, developed an index to measure employees' level of digitalization usage. Their findings indicate that digital transformation at the grassroots level positively impacts employee wages in Germany. Conversely, the study by Forman, Goldfarb, and Greenstein (2012) yields slightly different results. They found that technology is significantly associated with wage growth only in regions that are already affluent, highly educated, densely populated, and have IT-intensive industries, while it is unrelated to wages in other regions. Similarly, Caselli and Manning (2019) argue that new technology is unlikely to reduce wages across the board and that it can increase average wages if the prices of investment goods fall relative to consumer goods.

In addition to the impact of digital transformation, personal factors also play a significant role in influencing income. These factors include demographic characteristics such as age and gender, as well as education, work experience, and personality traits (Becker & Tomes, 1986; Cain, 1986; Card, 1995; Mincer, 1975). Various studies have offered different explanations for income gaps. Some suggest that such disparities arise from discrimination, while others highlight differences in human capital or labor productivity. Notably, income differences driven by human capital or labor productivity are often regarded as positive, as they contribute to economic development. Mincer (1974) emphasized the pivotal role of human capital in economic development. He argued that an individual's current income depends on their past investments in human capital. In other words, workers' income tends to increase with additional years of education and work experience. Building on this perspective, Becker and Tomes (1986) demonstrated that income inequality is linked to differences in education and training and is further influenced by individual talents, family background, and inheritance factors that vary across individuals. Becker described education as a key factor in explaining income variation, noting that it not only raises wages but also enhances health and shapes individuals' attitudes toward achieving a better quality of life (Becker & Tomes, 1986).

In addition, many empirical studies confirm that individual characteristics (human capital) can help workers enhance productivity, increase their employability, and improve personal income (Koch & McGrath, 1996; Vinokur, Schul, Vuori, & Price, 2000). Most studies have observed income disparities based on gender (Abe, 2010; Ahmed &

Maitra, 2010; Arulampalam, Booth, & Bryan, 2007; Figueiredo & Botelho, 2013; Leone & Cascio, 2020; Nestić, 2010; Onozuka, 2016). Furthermore, research consistently shows that individuals with higher levels of education and expertise tend to have higher incomes, lower unemployment rates, and are more likely to work in prestigious occupations compared to those with lower levels of education (Alsulami, 2018; Fang & Sakellariou, 2016; Mishra & Smyth, 2015; Mocan, 2013; Wannakrairoj, 2013).

2.2. The Income Gap Between Formal and Informal Workers

Numerous studies have examined the income gap between formal and informal workers, with most findings highlighting significant wage differences between the two (Daza & Gamboa, 2013; Mønsted, 2000; Sookram & Watson, 2008). Mønsted (2000) in a study on wages in Bolivia, it was argued that the gap between formal and informal workers was mainly driven by differences in education and experience. In Trinidad and Tobago, Sookram and Watson (2008) also found that formal workers earned higher incomes, with experience being the decisive factor. Similar findings were reported in Brazil, South Africa, and Mexico (Bargain & Kwenda, 2014), Colombia (Daza & Gamboa, 2013) and India (Singhari & Madheswaran, 2017). Beyond education and experience, other factors have also been highlighted, such as gender and occupation (Kumar & Pandey, 2021) as well as wage-setting mechanisms and institutional barriers (Meghir, Narita, & Robin, 2015; Ulyssea, 2018).

In summary, international studies have examined income inequality from various perspectives, including personal characteristics, gender, occupation, and institutional factors. However, in the context of digital transformation, the income gap between formal and informal workers has received limited attention. This study, therefore, focuses on analyzing the wage gap between formal and informal workers while explaining income disparity through the lens of digital transformation and individual-level factors. The results are expected to offer valuable insights for the development of wage policies in Vietnam.

2.3. Data Description

This study utilizes data from the Labor Force Survey (LFS) and the ICT index. The LFS is an annual survey conducted by the General Statistics Office of Vietnam, aimed at systematically monitoring and assessing key information on the Vietnamese labor market. The survey covers households and all household members nationwide, employing a stratified random sampling method with technical support from the International Labour Organization (ILO). In 2022, the LFS recorded more than 800,000 observations across all age groups and labor statuses. For this study, only individuals of working age (from 19 to 64) who were employed were retained, and observations with missing information on income, education, or work experience were excluded. After cleaning, the final sample consisted of 342,793 observations.

In addition to the LFS, digital transformation is measured using the ICT index, which is published annually by the MIC (2022) and developed based on the United Nations EGDI framework. The index reflects the level of digital transformation readiness in each locality and is composed of three key components: *Technical_infrastructure*, *Human_infrastructure*, and *IT_infrastructure*. As a provincial-level index, it captures both the technological context faced by workers and the digital capacity of local authorities at the time of the survey.

This measurement approach differs significantly from studies such as Acemoglu and Restrepo (2020) which uses data on industrial robots at the industry level to capture the degree of automation and labor displacement in advanced economies. While their work focuses on the direct effects of automation on employment, the ICT index used in this study reflects broader digital readiness across regions. This distinction is shaped by both data availability and economic context: in Vietnam, where detailed enterprise-level data are limited, the ICT index provides a valuable proxy for assessing digital transformation, especially in research involving the informal sector.

The descriptive statistics for the variables by region are presented in Table 1:

Table 1. Descriptive statistics of variables by region.

Variables	Variable name explanation	Coding/Scale	Data source	Mean		
				Total	Formal	Informal
Lnwage	Logarithm of workers' monthly income	Continuous, log of monthly income	General Statistics Office of Vietnam (GSO) (2022)	8.718	8.961	8.600
Work_experience	Work experience	Ordinal, 0–6 (Levels of working time)	General Statistics Office of Vietnam (GSO) (2022)	4.177	4.118	4.206
Gender	Gender of the worker	Dummy, 1 = male, 0 = female	General Statistics Office of Vietnam (GSO) (2022)	0.552	0.465	0.594
Vocational	Highest education: vocational	Dummy, 1 = Yes, 0 = No	General Statistics Office of Vietnam (GSO) (2022)	0.056	0.105	0.032
College/University	Highest education: college or university	Dummy, 1 = Yes, 0 = No	General Statistics Office of Vietnam (GSO) (2022)	0.190	0.473	0.052
Postgraduate	Highest education: postgraduate	Dummy, 1 = Yes, 0 = No	General Statistics Office of Vietnam (GSO) (2022)	0.010	0.028	0.001
IT_use_individual	Workers who use information technology in their jobs	Dummy, 1 = Yes, 0 = No	General Statistics Office of Vietnam (GSO) (2022)	0.201	0.458	0.076
Techical_infrastructure	Technical infrastructure in the locality	Normalized index (0–1)	MIC (2022)	0.544	0.546	0.544
Human_infrastructure	Human resources infrastructre in the locality	Normalized index (0–1)	MIC (2022)	0.420	0.413	0.423
IT_infrastructure	Information technology infrastructre in the locality	Normalized index (0–1)	MIC (2022)	0.430	0.429	0.430
	Observations			342,973	230,966	112,007

Note: For binary variables, the mean represents the proportion of individuals with the value of 1. For continuous variables, the mean is the arithmetic average.

3. RESEARCH METHODOLOGY

This study adopts the income function developed by Mincer (1975) and extends it following the approach of Card (1995). This is a classic method in labor economics, commonly used to analyze the effects of individual characteristics such as education, work experience, and technology proficiency on income. The model is specified in a log-linear (log-lin) form, which allows for the estimation of semi-elasticities between explanatory variables and income. This functional form is particularly suitable for large-scale cross-sectional data, such as the Labor Force Survey (LFS) in Vietnam, and is adaptable to advanced econometric techniques, including quantile regression and two-stage least squares (2SLS), to address issues of endogeneity and heterogeneity in income distribution. The income function is represented by the following equation,

$$lnW_i = \beta X_i + \varepsilon_i \qquad (1)$$

Here, lnW_i represents the logarithm of monthly income, X_i is the vector of explanatory variables, β denotes the regression coefficients to be estimated, and ε_i is the error term.

Equation (1) is estimated using quantile regression, as introduced by Koenker and Bassett (1978). This method allows for a more detailed analysis of the relationship between income and its influencing factors at different quantiles of the income distribution, offering a more comprehensive perspective compared to OLS regression. The conditional quantile regression equation of W on X at quantile τ is expressed as follows.:

$$lnW_i = \beta_\tau X_i + \varepsilon_i \qquad (2)$$

Where $\beta\tau$ represents the regression coefficient at the τ quantile. The regression will be conducted at key quantiles, including 0.1, 0.25, 0.5, 0.75, and 0.9. Specifically, the 0.1 and 0.9 quantiles represent low-income and high-income groups, respectively, while the median quantile (0.5) reflects the average income level.

Subsequently, the Machado and Mata decomposition method is employed to measure and analyze the income gap between workers in the formal and informal sectors (Machado & Mata, 2005). This method represents a significant improvement over the approach developed by Oaxaca (1973) which only allows for decomposition at the mean level. In contrast, the Machado and Mata method enables the decomposition of income differences across the entire income distribution. This feature makes it especially suitable in the context of rising income inequality and the presence of a non-normal income distribution. The decomposition equation is expressed as follows:

$$LnW_f - LnW_i = (\beta_{\tau f} - \beta_{\tau i})\, X_f + (X_f - X_i)\, \beta_{\tau i} \qquad (3)$$

In the equation, f and i refer to workers in the formal and informal sectors, respectively. $\beta_{\tau f}$ and $\beta_{\tau i}$ are regression coefficients at the τ percentile for each group. The term $(\beta_{\tau f} - \beta_{\tau i})\, X_f$ represents the difference attributable to variations in regression coefficients, while the term $(X_f - X_i)\, \beta_{\tau i}$ reflects the difference arising from disparities in labor characteristics.

Building on the extended form of the Mincer income function and the availability of existing data, this study employs the logarithm of monthly income as the dependent variable in the income function. The explanatory variables included in the regression model are professional qualifications (Vocational, College/University, Postgraduate), gender, work experience, individual ability to use information technology at work, and the level of digital transformation in the economy, measured through technical infrastructure, human infrastructure, and IT infrastructure. Since the dependent variable is in logarithmic form, the regression coefficients in the log-linear model are interpreted as percentage changes using the formula (e^β – 1) × 100, where β represents the estimated coefficient of each explanatory variable (Wooldridge, 2010).

In income analysis models, many studies have shown that variables related to working time, such as work experience or working hours, may be endogenous due to their interaction with income (Anh, 2015; Wolf, 2000). Similarly, in this study, the variable representing work experience (*Work_experience*) is identified as potentially endogenous, as workers with higher incomes may remain employed longer, thereby increasing their accumulated experience. To address this issue, the study applies the two-stage least squares (2SLS) method using two instrumental variables: birth year (*birthyear*) and place of residence (*prov*). The year of birth is closely linked to potential work experience, as individuals born earlier generally have more years of participation in the labor market. Once we control for education, gender, and personal skills, we argue that birth year no longer has a direct impact on current income, but rather affects it indirectly through experience. Similarly, place of residence reflects characteristics of the local labor market, such as job opportunities or infrastructure development, which may influence the length of employment. However, after including personal attributes and provincial ICT indicators in the model, the direct effect of residence on income is expected to be minimal.

Based on these arguments, *birthyear* and *prov* can be considered valid instruments that satisfy the exclusion restriction. This means they influence the endogenous variable (*Work_experience*) but do not have a direct effect on income. This approach is consistent with a number of labor studies that have employed demographic or regional characteristics as instruments for work experience (Angrist & Krueger, 1991; Card, 1993; Duflo, 2001).

4. RESULTS AND DISCUSSIONS

Before running the income regressions for the two sectors, the study checks whether *Work_experience* is endogenous by using a two-stage least squares (2SLS) approach with *birthyear* and *prov* as instruments. The first-stage results show that both instruments are strongly related to *Work_experience* (see Appendix 1). Based on this, the study proceeds to the second stage, where it uses the predicted values of Work_experience from the first stage to estimate the final regression model and correct for endogeneity (see Appendix 2). At the same time, the Durbin–Wu–Hausman test confirms that *Work_experience* is endogenous at a high level of significance (Appendix 3). Therefore, applying 2SLS with these two instruments is a reasonable choice to improve the consistency of the estimates. These results provide a solid basis for subsequent analyses, particularly the quantile regressions with instruments that aim to capture income differences between formal and informal workers.

Tables 2 and 3 present the income regression results for the informal and formal sectors.

Table 2. Estimates of workers' income by quantile regression, informal sector, 2022.

Independent variables	2SLS	2SQR - two-step quantile regression				
		10%	25%	50%	75%	90%
ln_Work_experience	-0.02 (-0.36)	-0.191* (-2.17)	-0.210* (-2.45)	-0.02 (-0.32)	0.11 (1.66)	0.270** (2.93)
ln_Gender	0.323*** (59.99)	0.435*** (42.82)	0.362*** (40.70)	0.284*** (66.34)	0.221*** (46.40)	0.223*** (31.60)
ln_IT_use_individual	0.398*** (20.52)	0.404*** (13.79)	0.291*** (11.56)	0.293*** (13.77)	0.391*** (19.82)	0.423*** (13.82)
ln_Vocational	0.139*** (14.94)	0.127*** (5.09)	0.0983*** (7.70)	0.119*** (15.41)	0.162*** (15.20)	0.164*** (11.56)
ln_College/University	0.239*** (10.72)	0.198*** (4.87)	0.128*** (3.66)	0.196*** (9.45)	0.274*** (10.21)	0.316*** (9.86)
ln_Postgraduate	0.278*** (6.10)	0.519** (2.79)	0.466*** (5.76)	0.360*** (9.43)	0.193** (2.99)	0.15 (0.88)
ln_Technical_infrastructure	0.117*** (4.21)	0.349*** (8.37)	0.223*** (6.54)	0.110*** (4.18)	0.0943** (2.74)	0.04 (1.12)
ln_Human_infrastructure	-0.124*** (-7.50)	-0.157*** (-4.00)	-0.148*** (-5.55)	-0.185*** (-9.16)	-0.155*** (-11.07)	-0.158*** (-6.19)
ln_IT_infrastructure	-0.0414** (-2.83)	-0.287*** (-6.81)	-0.0896*** (-4.32)	0.01 (0.50)	0.03 (1.81)	0.03 (1.07)
_cons	8.457*** (35.21)	8.226*** (21.90)	8.840*** (25.36)	8.560*** (35.63)	8.359*** (31.14)	8.105*** (21.12)
N	230,966	230,966	230,966	230,966	230,966	230,966

Note: Numbers in parentheses are t-statistics.
Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 3. Estimates of workers' income by quantile regression, formal sector, 2022.

Independent variables	2SLS	2SQR - two-step quantile regression				
		10%	25%	50%	75%	90%
Work_experience	0.221*** (3.35)	0.34 (1.73)	0.346*** (4.26)	0.188* (2.47)	0.11 (1.68)	0.178* (2.14)
Gender	0.144*** (64.79)	0.0882*** (23.07)	0.115*** (26.66)	0.142*** (46.96)	0.166*** (48.38)	0.193*** (54.85)
IT_use_individual	0.0662*** (9.17)	0.04 (1.57)	0.0275** (2.91)	0.0590*** (8.32)	0.0923*** (15.38)	0.0953*** (10.21)
Vocational	-0.099*** (-3.77)	-0.167* (-2.35)	-0.147*** (-4.75)	-0.0756** (-2.75)	-0.01 (-0.51)	-0.05 (-1.24)
College/University	0.0655** (2.84)	-0.002 (-0.03)	-0.019 (-0.75)	0.05 (1.91)	0.134*** (5.90)	0.158*** (4.55)
Postgraduate	0.153*** (7.18)	0.11 (1.89)	0.105*** (3.40)	0.161*** (6.98)	0.206*** (9.59)	0.204*** (8.53)
Technical_infrastructure	0.321*** (25.82)	0.177*** (3.50)	0.209*** (10.78)	0.295*** (18.33)	0.365*** (25.29)	0.463*** (21.12)
Human_infrastructure	-0.256*** (-17.45)	-0.122*** (-6.74)	-0.159*** (-7.23)	-0.177*** (-9.37)	-0.220*** (-9.94)	-0.409*** (-15.02)
IT_infrastructure	-0.149*** (-12.14)	-0.159*** (-7.35)	-0.177*** (-6.93)	-0.173*** (-9.97)	-0.176*** (-12.53)	-0.165*** (-9.39)
_cons	7.922*** (32.17)	7.093*** (9.89)	7.267*** (24.20)	8.056*** (28.04)	8.503*** (36.15)	8.434*** (27.66)
N	112,007	112,007	112,007	112,007	112,007	112,007

Note: Numbers in parentheses are t-statistics.
Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The regression results from the two tables above will be presented in graphical form to facilitate the comparison of regression coefficients between workers in the informal and formal sectors. In all the graphs below, the horizontal axis represents the percentiles of the regression, corresponding to worker groups with income levels ranging from low to high. The vertical axis displays the values of the regression coefficients at different percentiles, illustrating the income gap between the two groups of workers based on the explanatory variables.

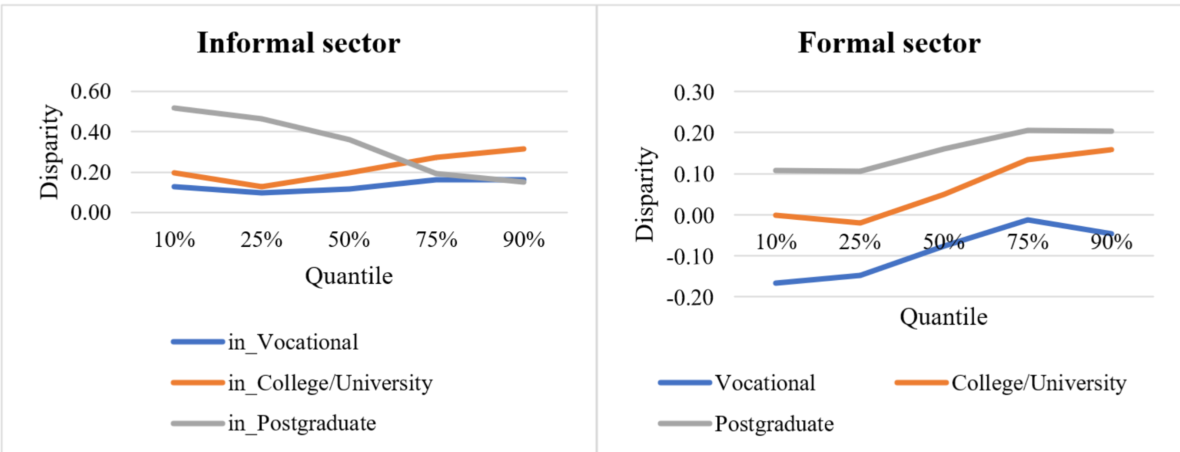

Figure 3. Regression coefficient by degree.

Figure 3 illustrates the regression coefficients of dummy variables representing education levels for two groups of workers: those in the informal sector and those in the formal sector.

In the informal sector, the income gap among workers with different educational levels is substantial at lower quantiles. Specifically, at the 10th percentile, workers with postgraduate qualifications earn approximately 45% more than those with intermediate qualifications and 28% more than those with college or university degrees. However, at higher percentiles (75%–90%), this gap gradually narrows, indicating that highly educated workers are unable to maintain their advantage at higher income levels. This reflects the reality that, at low income levels, less-educated workers often engage in simple, temporary, and unprotected jobs, resulting in significant disadvantages (Nhat Duong, 2024). In contrast, at higher income levels, earnings are influenced by educational qualifications, as well as by experience, practical skills, personal networks, and entrepreneurial ability.

Unlike the informal sector, the income gap among workers with different educational levels in the formal sector is consistently maintained across all income levels. Workers with higher educational attainment consistently earn more, particularly those with postgraduate qualifications. Specifically, workers holding postgraduate degrees exhibit the highest stable and positive regression coefficients across all quantiles, ranging from 0.11 at the 10th percentile to approximately 0.20 at the 90th percentile. This indicates that they earn significantly more than workers with lower levels of education. Meanwhile, vocationally trained workers show a negative coefficient at the lower end of the distribution (–0.18 at the 10th percentile), which only slightly increases to around 0.03 at the 90th percentile. This suggests that vocational education provides limited income advantages and may even be associated with lower earnings at the lower end of the income spectrum. These findings highlight that educational advantages are consistently maintained across the income distribution in the formal sector. In practice, the formal sector often enforces strict recruitment standards, where educational qualifications play a key role in assessing competency, determining salary levels, and providing promotion opportunities. Workers with higher degrees, especially postgraduate degrees, are typically assigned to specialized or managerial positions, enabling them to maintain stable and high incomes. In contrast, less-educated workers in this sector are often limited to simple jobs with minimal opportunities for advancement, resulting in lower income levels.

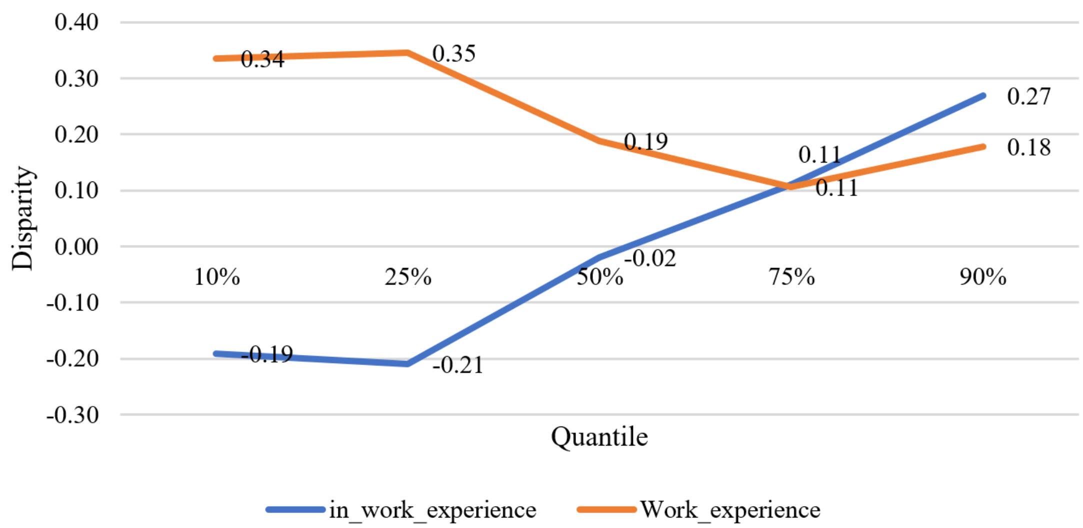

Figure 4. Regression coefficient by work experience.

Figure 4 illustrates that the relationship between work experience and income differs markedly between the two sectors. In the formal sector, the coefficient of this variable is consistently positive and remains relatively stable, ranging from 0.2 to 0.35 across all quantiles. This reflects the uniform contribution of experience to income growth. In contrast, in the informal sector, the effect of work experience on income varies significantly depending on the worker's position in the income distribution. Specifically, within the low-income group (10th to 50th quantile), the regression coefficient for work experience is negative, indicating that additional experience does not lead to higher earnings. This may reflect job instability or limited opportunities for wage progression. Only from the 75th quantile onward does the coefficient become positive and gradually increase, reaching approximately 0.28 at the 90th quantile. These findings suggest that work experience becomes an income advantage primarily for high-income informal workers, those likely to remain in employment longer, who possess adaptable competencies and have greater access to economic opportunities.

This difference can be attributed to the characteristics of each sector. Workers in the informal sector are often concentrated in occupations that do not require high qualifications, such as small-scale trading or seasonal labor, where seniority does not provide a significant income advantage. However, for self-employed workers or those in specialized fields such as machinery repair or commercial activities, long-term experience can help them build a reputation and establish a customer network, resulting in higher incomes compared to newcomers. In contrast, workers in the formal sector are often protected by labor policies, including long-term contracts, social insurance, and regular salary increments (ILO, 2021). Nevertheless, to achieve higher salaries in this sector, workers must also possess additional attributes such as professional expertise, work performance, and soft skills.

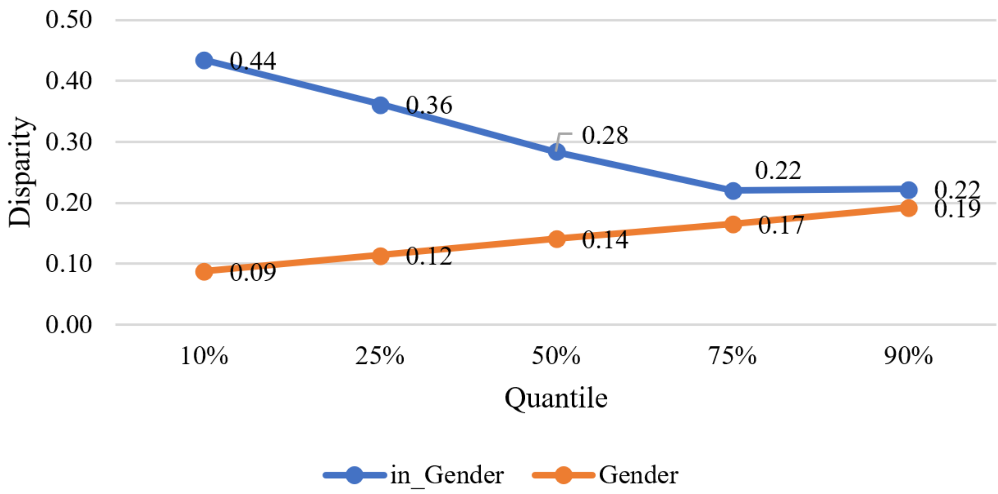

Figure 5. Regression coefficient by gender.

Figure 5 provides a valuable perspective on the gender income gap between workers in the formal and informal sectors, highlighting the persistence of gender inequality. The analysis indicates that men consistently earn higher incomes than women across all income groups. However, the trend in the income gap between genders varies significantly between the two labor sectors. In the informal sector, the gender income gap gradually narrows as income levels increase. This trend partly reflects that in fields such as handicrafts, beauty care, or self-employment, female workers can achieve high earnings due to their skills and dexterity, thereby reducing the gap relative to men. In contrast, in the formal sector, the income disparity tends to widen among high-income groups, possibly due to barriers to women's career advancement. Grant Thornton (2019b) identifies several obstacles for female leaders in Vietnam, including limited career development opportunities (Global: 27%; Vietnam: 40%), restricted networking (Global: 26%; Vietnam: 35%), family responsibilities outside of work (Global: 25%; Vietnam: 39%), and insufficient time to take on key job responsibilities (Global: 32%; Vietnam: 35%). These challenges not only hinder women's career progression but also limit their ability to enhance their skills, thereby restricting their professional success. As evidence, only 15% of businesses worldwide have women in CEO or Managing Director positions (Grant Thornton, 2019a). While this proportion has improved in recent years, gender equality in senior leadership remains a distant goal.

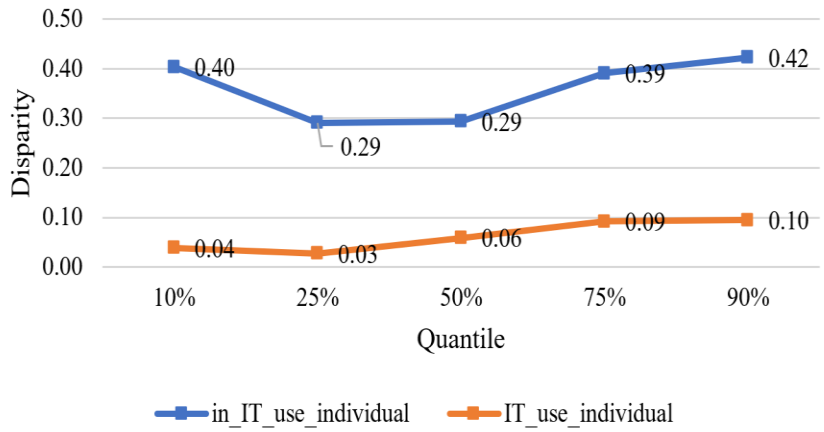

Figure 6. Regression coefficient by information technology.

The income gap between workers who use information technology (IT) and those who do not differs significantly between the informal and formal sectors (Figure 6). In the informal sector, workers who apply IT earn considerably higher incomes than those who do not across all income quantiles. Specifically, at the 10th quantile, the regression coefficient is approximately 0.41, corresponding to an income increase of about 50 percent. At the 90th quantile, this coefficient rises to nearly 0.45, equivalent to an income increase of about 57 percent. These findings suggest that, in the context of widespread digital transformation, particularly within the highly flexible informal sector, IT proficiency provides a clear advantage in accessing new work platforms, expanding client networks, and improving productivity. Many high-paying jobs in this sector now rely heavily on technological engagement, such as e-commerce, gig-based delivery services, or freelancing through digital platforms. Therefore, the higher income among workers with IT skills likely reflects their better adaptation to the digital labor environment and their capacity to take advantage of emerging market opportunities.

In contrast, in the formal sector, the regression coefficient for IT use is notably smaller, ranging from 0.03 to 0.10, corresponding to an earnings increase of only 3 percent to approximately 10 percent. This may be attributed to the homogeneity of IT proficiency among workers in this sector, as basic IT skills are often part of standard recruitment requirements. When proficiency levels are relatively uniform, the marginal effect of IT proficiency on earnings becomes limited.

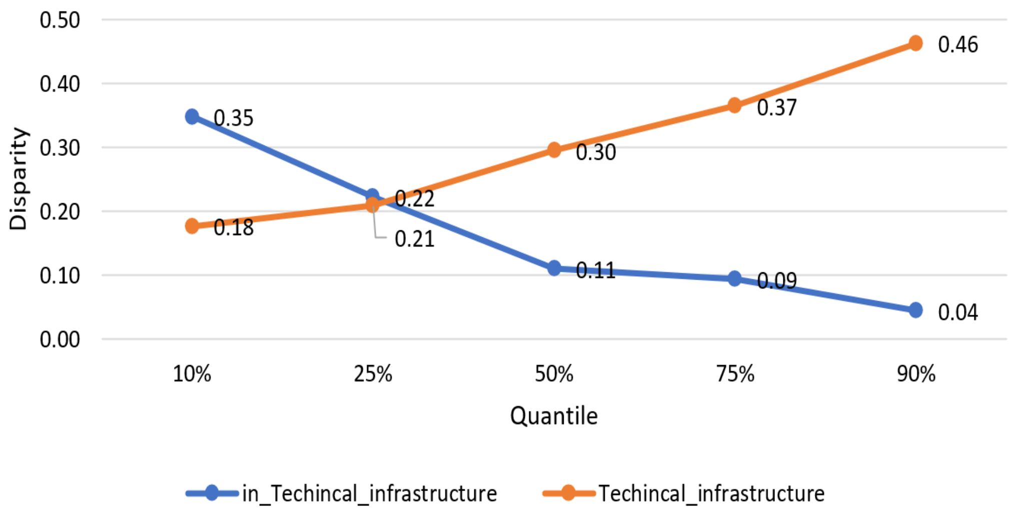

Figure 7. Regression coefficient by technical infrastructure.

Digital transformation presents a multidimensional perspective on workers' income. In theory, it has the potential to significantly impact the economy and create numerous opportunities for income improvement. However, as a public asset, digital transformation is accessible to all. This study incorporates digital transformation into the model to assess the extent to which digital platforms contribute to workers' income generation. The regression results in Tables 2 and 3, however, it is suggested that human infrastructure and IT infrastructure do not provide direct value to workers in either the informal or formal sectors. This finding is reasonable, as these indicators are measured based on the proportion of officials and civil servants in public agencies who hold IT-related degrees or use email for work. As such, they primarily reflect the overall efficiency of the state apparatus rather than the productivity of individual workers in the economy. In other words, digital transformation in the public sector has not yet strongly spilled over into the private labor market, so it has not made a clear impact on workers' incomes.

The technical infrastructure index (Figure 7), calculated based on the proportion of households with broadband internet access, directly influences workers' income at the household level. In the formal sector, the regression coefficient of the technical infrastructure index increases progressively across income quantiles, indicating that formal workers effectively leverage the opportunities presented by the digital economy. In contrast, in the informal sector, technical infrastructure positively impacts the income of workers in the lower quantiles, but this effect diminishes at higher income levels. In lower-income groups, the expansion of technical infrastructure can lead to the decline of traditional and manual jobs, displacing low-skilled workers. At the same time, it creates opportunities for new types of employment that require a basic understanding of technology (Phuc, 2024). This shift poses challenges for low-skilled workers, who face increased competition and the need to adapt to new labor market demands. At higher income levels, however, workers' earnings depend not only on their ability to apply technology often relevant to sales, online delivery, and ride-hailing but also on other factors such as professional qualifications and soft skills, particularly in fields like finance, insurance, and content creation.

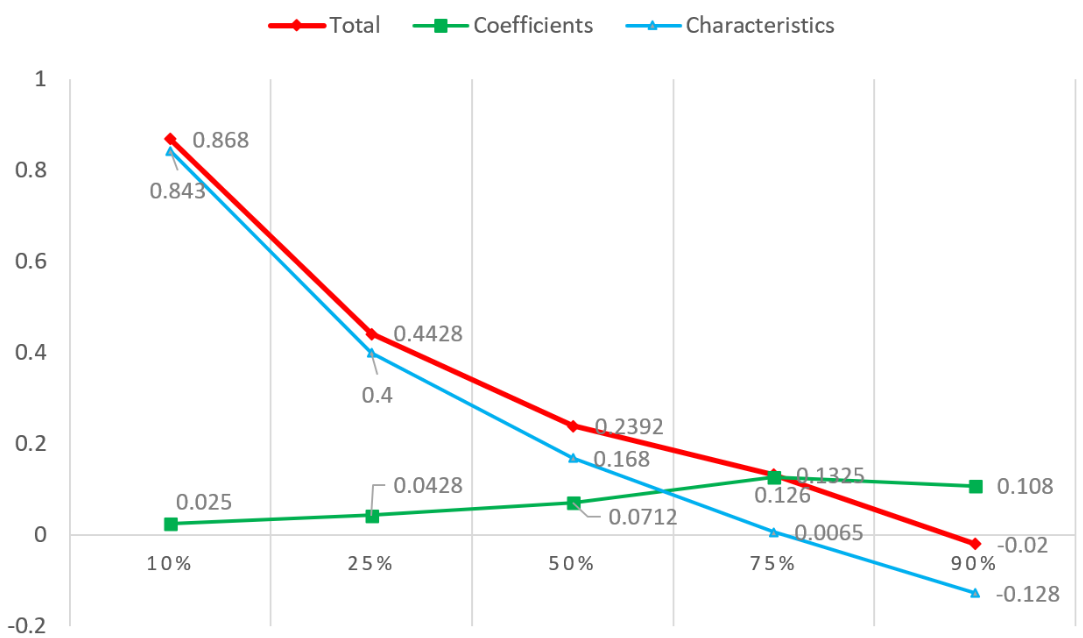

Figure 8. Decomposition of wage disparities by labor group in Vietnam, 2022.

Finally, Figure 8 presents an examination of the income gap between informal workers and formal workers. Overall, formal workers tend to earn higher wages than their informal counterparts across most income quantiles. This disparity primarily results from differences in labor characteristics, with a trend similar to the overall income gap curve, while variations in the regression coefficient across quantiles are relatively minor. Notably, formal workers earn higher incomes in the lower quantiles, experience a decline in the middle quantile, and have lower incomes in the highest quantile. This pattern suggests that at higher income levels, informal workers may achieve high earnings through self-employment or jobs that leverage personal skills, professional networks, or flexible work arrangements. In contrast, formal workers in this category may face salary ceilings or organizational regulations that limit their earning potential.

5. CONCLUSIONS AND RECOMMENDATIONS

The regression results indicate that the income gap between formal and informal workers in Vietnam is largely explained by differences in education, gender, and digital skills, while the impact of digital transformation remains limited. A key contribution of this study is the integration of micro-level labor data with provincial ICT indicators, providing empirical evidence that digital transformation in the public sector has not yet significantly spilled over into enterprises and the labor market. Based on these findings, the authors propose three groups of policy recommendations to narrow the income gap between formal and informal workers:

First, enhancing the effectiveness of digital transformation. The government should invest more heavily in digital infrastructure (such as high-speed internet, online public services, and data centers) while encouraging businesses to expand the adoption of digital technologies in production and business activities. A more integrated digital environment would create broader market access opportunities for both formal and informal workers.

Second, upgrading skills and protecting informal workers. Local authorities should collaborate with businesses and social organizations to deliver hands-on digital skills training (e.g., electronic payments, online commerce, and personal finance management). Special attention should be paid to reducing the gender gap in digital skills by designing flexible training programs in terms of time and location or by providing financial support for women, who often face greater barriers to accessing technology. Alongside training, the government should expand flexible forms of social and health insurance to mitigate risks and encourage informal workers to invest in their own capacity to participate more effectively in the labor market.

Third, improving the wage system in the formal sector. The government should accelerate wage reform toward greater flexibility, linking pay to productivity and actual contributions rather than relying solely on seniority. A more attractive and fair wage system would not only increase the motivation of formal workers but also make the formal sector more appealing for informal workers seeking stable and better-protected employment.

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Appendix 1. First-stage regression.

Work_experience	Coefficient	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Gender	0.067	0.003	21.610	0.000	0.061	0.073
IT_use_individual	-0.067	0.005	-13.460	0.000	-0.077	-0.057
Vocational	0.129	0.007	18.800	0.000	0.115	0.142
College_University	0.071	0.005	13.900	0.000	0.061	0.081
Postgraduate	0.373	0.016	23.150	0.000	0.341	0.404
Technical_infrastructure	0.229	0.016	13.960	0.000	0.197	0.261
Human_infrastructure	0.065	0.016	4.040	0.000	0.034	0.097
IT_infrastructure	-0.020	0.015	-1.390	0.164	-0.049	0.008
Birthyear	0.000	0.000	-14.510	0.000	0.000	0.000
Prov	-0.001	0.000	-21.940	0.000	-0.001	-0.001
_cons	4.200	0.013	320.000	0.000	4.174	4.226

Appendix 2. Instrumental variable 2SLS regression.

Lnwage	Coefficient	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Work_experience	-1.162	0.051	-22.48	0.000	-1.264	-1.061
Gender	0.320	0.005	58.610	0.000	0.031	0.331
IT_use_individual	0.192	0.007	25.280	0.000	0.177	0.207
Vocational	0.266	0.011	22.520	0.000	0.243	0.289
College_University	0.346	0.008	43.010	0.000	0.330	0.361
Postgraduate	0.648	0.029	21.920	0.000	0.590	0.706
Technical_infrastructure	0.506	0.026	19.270	0.000	0.454	0.558
Human_infrastructure	-0.221	0.021	-10.320	0.000	-0.263	-0.179
IT_infrastructure	-0.108	0.019	-5.460	0.000	-0.147	-0.695
_cons	13.138	0.206	63.540	0.000	12.732	13.543

Appendix 3. Test of endogeneity.

Test	Statistic	df	P-value
Durbin (score) χ^2	2153.5	-1	0
Wu–Hausman F	2167.04	-1,342,962	0